

MODEL-INDEPENDENT VELOCITY AND ACCELERATION OF HELIOSPHERIC DISTURBANCES

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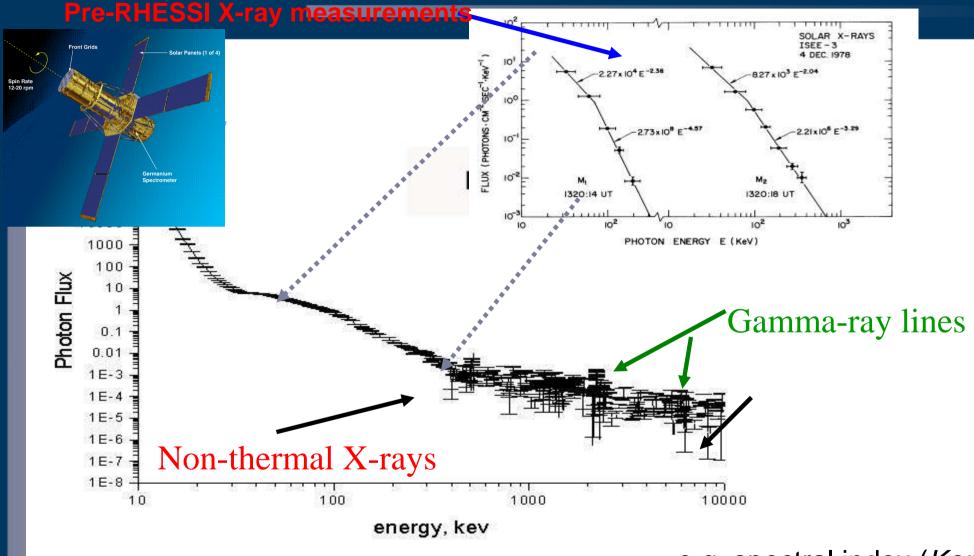
Prologue...

"Acceleration errors are difficult..."

Angelos Vourlidas



Motivation – X-ray data

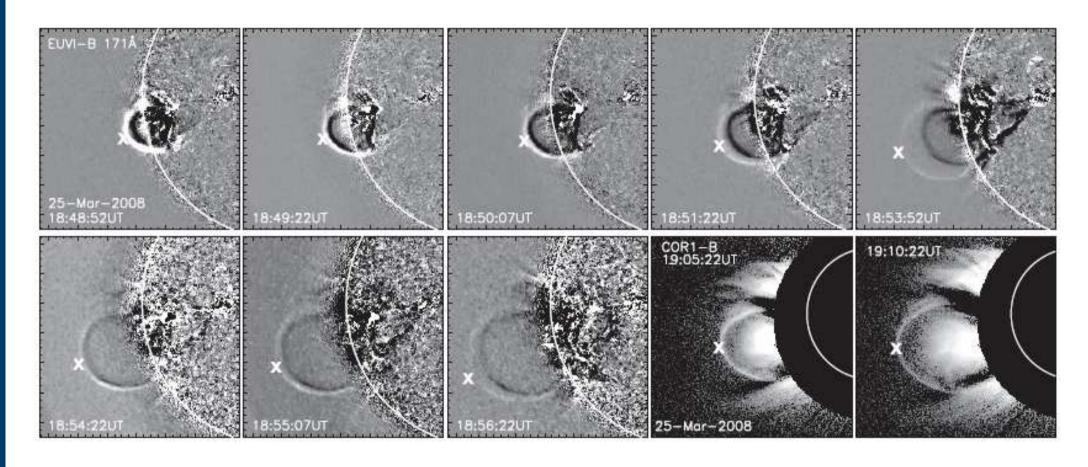


Ramaty High Energy
Solar Spectroscopic Imager(RHESSI)

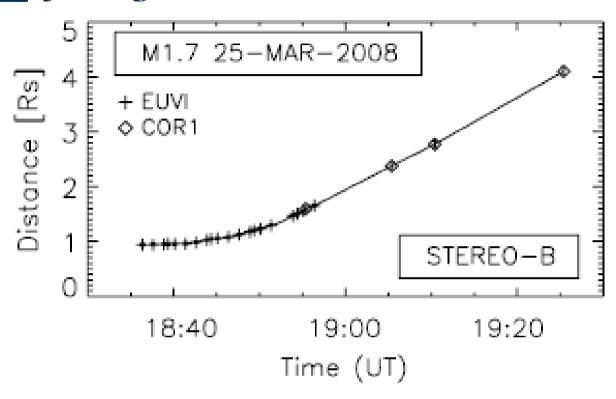
e.g. spectral index (Kontar and MacKinnon, 2005)



Let us consider CME propagation....



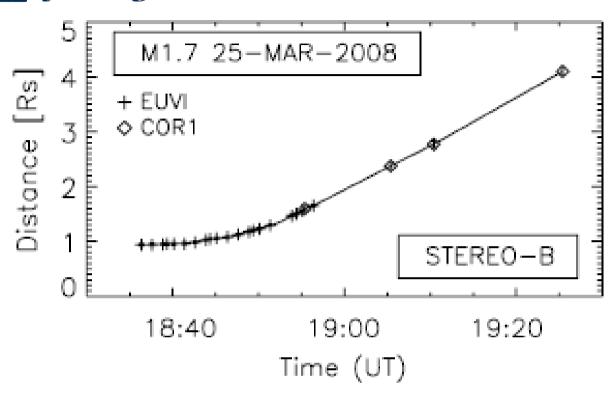
2008 March 25, M1.7 flare/CME event observed with STEREO-B from (Temmer et al, ApJ, 2010)



Distance vs time for 2008 March 25, M1.7 flare/CME event observed with STEREO-B from (Temmer et al, ApJ, 2010)

Two approaches to find velocity and acceleration of CMEs:

- 1) Forward fitting: to find the parameters of the model as a best fit to the original data
- 2) Model independent (**no model assumed**) inference of velocity and acceleration



Distance vs time for 2008 March 25, M1.7 flare/CME event observed with STEREO-B from (Temmer et al, ApJ, 2010)

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Let us assume that we have a analytical functions h(t) over the finite time interval (t_0, t_N) , while we are given a dataset of height measurements:

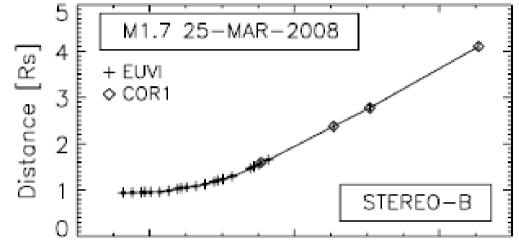
$$h_i$$
, $i = 1...N$
for a number of times t_i , $i = 1...N$.

The dataset has a finite uncertainty of the measurements δh , so that

$$h_i - h(t_i) < \delta h$$

Now our problem is to find the best smooth representations of

$$v(t)=dh(t)/dt$$
 (velocity)
 $a(t)=d^2h(t)/dt^2$ (acceleration)





Derivative as an inverse problem

The problem of finding derivative can be written as the integral inversion problem (*Groetsch, C. W. 1984, Hanke, M., & Scherzer, O. 2001*)

Indeed, the height at a given time is given by an integral

$$h_i = h_0 + \int_{t_0}^{t_i} v(t')dt'$$

we can re-write this equation in the matrix form

$$\mathbf{h} - h_0 = \mathbf{S}\mathbf{v}$$

where **S** is the matrix representing our integral

h is the data-vector given $[h_1, ..., h_N]$,

v is the velocity-vector to be found $[v_1, ..., v_M]$,

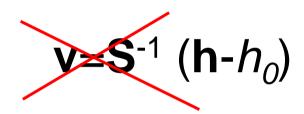
Regularized solution of inverse problem

In other words we are looking for a solution of the minimization problem

$$\|\mathbf{h} - h_0 - \mathbf{S}\mathbf{v}\|^2 = min$$

where $\|\cdot\|^2$ is a norm defined as $\|\mathbf{h}\|^2 \equiv \mathbf{h}^T \mathbf{h}$.

This problem [1] does not have a unique solution and additional constraints are needed (e.g. Berterro et al, 1985).



Using Tikhonov regularization technique (*Tikhonov, 1963*), our problem becomes:

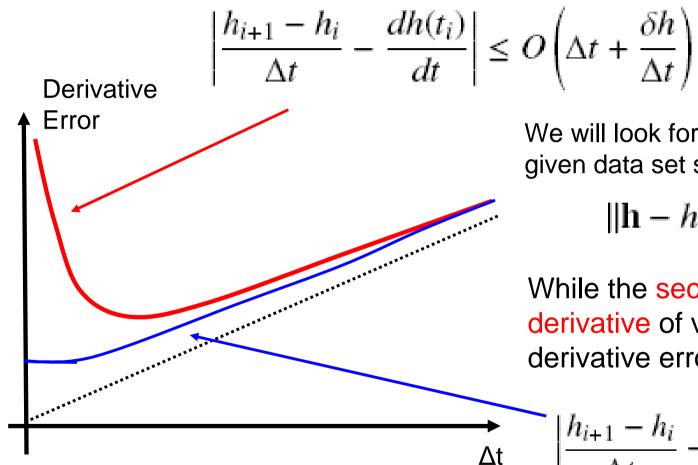
$$\|\mathbf{h} - h_0 - \mathbf{S}\mathbf{v}\|^2 + \lambda \|\mathbf{L}\mathbf{v}\|^2 = \min$$
 [2]

where L is the matrix representation of constraint operator, and λ is a regularization constant.

Importantly, the problem [2] is well-behaved and has a unique solution.

What is constraint matrix L?

The derivative error calculated from noisy data set:



We will look for a function h(t) close to a given data set so that

$$\|\mathbf{h} - h_0 - \mathbf{S}\mathbf{v}\|^2 = \|\delta h\|^2$$

While the second derivative of h(t) or first derivative of v(t) has a minimum, the derivative error looks much better:

Therefore, following Hanke and Scherzer (2001) we can choose L=D₁

The regularized solution

Hence we can write an explicit solution of minimization problem, which minimizes the amplification of the errors in the resulting estimate for the derivative, i.e. velocity:

$$\mathbf{v}_{\lambda} = \mathbf{R}(\mathbf{h} - h_0), \quad \text{where} \quad \mathbf{R} = (\mathbf{S}^T \mathbf{S} + \lambda \mathbf{D_1}^T \mathbf{D_1})^{-1} \mathbf{S}^T$$

The only unknown parameter is λ , which can be determined requiring the finite difference between our solution and the original dataset

$$\|\mathbf{h} - h_0 - \mathbf{S}\mathbf{v}_{\lambda}\|^2 = \alpha \|\delta\mathbf{h}\|^2$$

Parameter α tells us about the errors (should be around 1 in case of Gaussian errors)



The horizontal and vertical errors

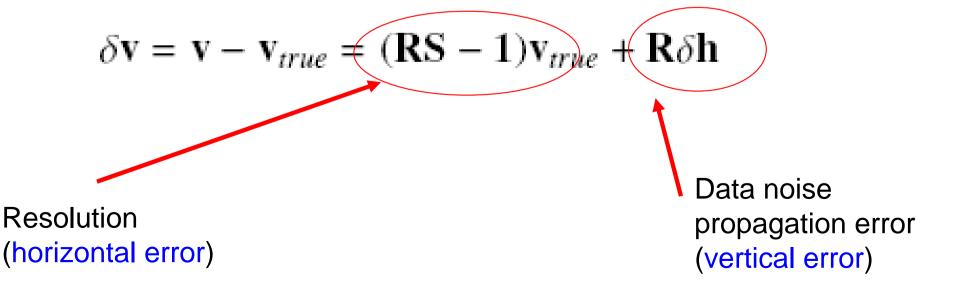
Let assume that we know the true solution of our linear inverse problem v_{true} , then we can write

$$\mathbf{h} - h_0 = \mathbf{S} \mathbf{v}_{true} + \delta \mathbf{h}$$

The regularized solution of our inverse problem is

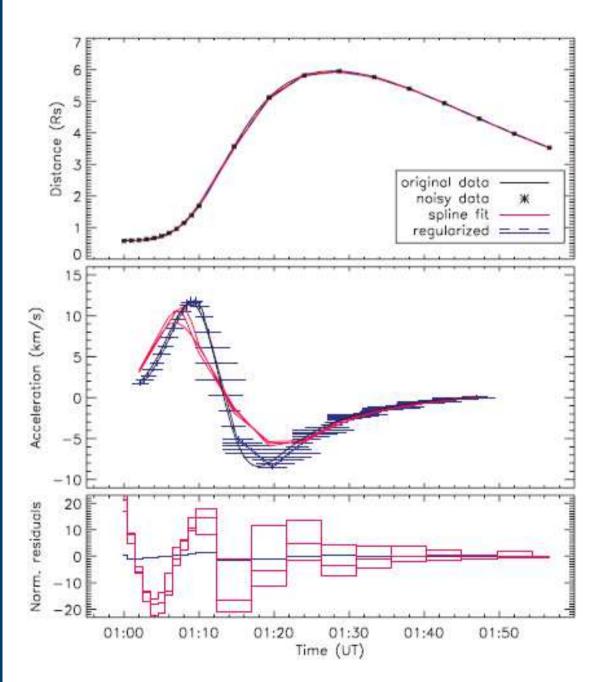
$$\mathbf{v} = \mathbf{R} \ (\mathbf{h} - h_0)$$

The difference between the true solution and our solution can be written as





Simulated data: example I



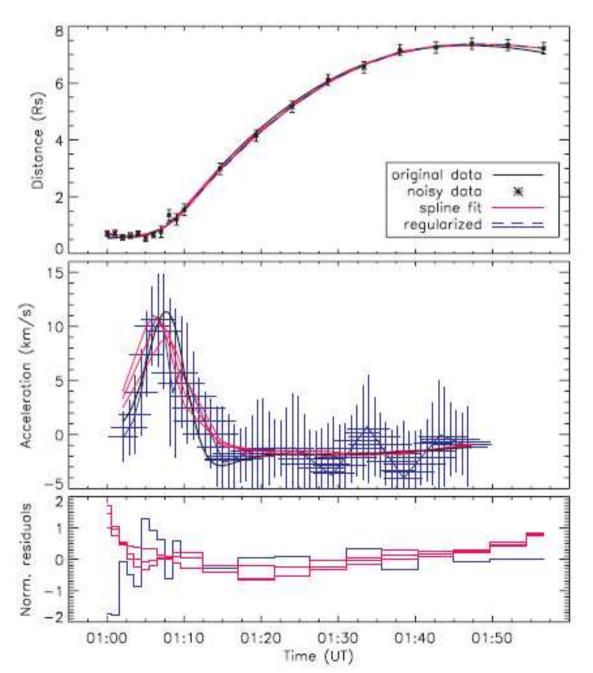
Simulated data (no noise added but discrete data set)

Acceleration profile (error due to discrete data set is evident)

Normalised residuals



Simulated data: example II

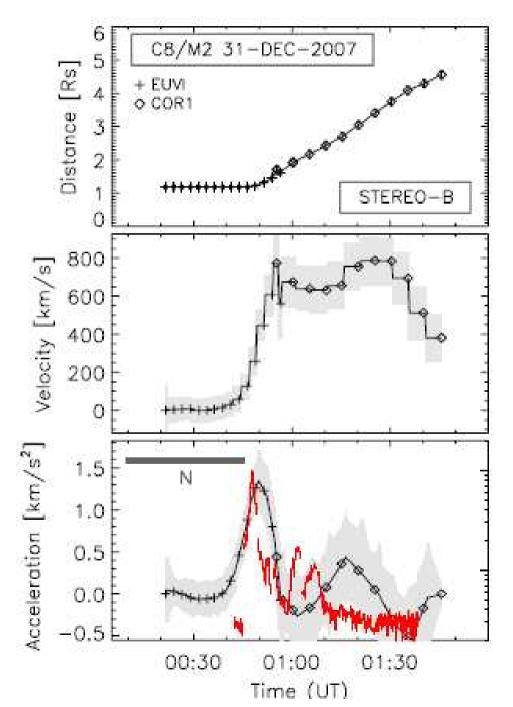


Simulated data (realistic noise added)

Acceleration profile

Normalised residuals

31-Dec-2007 flare/CME



Height-time data (Temmer et al, ApJ, 2010)

Velocity profile

Acceleration profile (Note change in acceleration profile)



Regularized inversion gives us model-independent (without assumptions on functional shape) velocity and acceleration as a function of time.

=>provides us with horizontal and vertical error bars and hence gives us confidence range for **velocity** and **acceleration**.

⇒Regularized derivative is IDL based package and easy to use

⇒Can be applied not only to CME data but to EIT waves etc